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Jing Deng
University of Colorado Boulder

Richard Han
University of Colorado Boulder

Shivakant Mishra
University of Colorado Boulder

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Jing Deng Richard Han Shivakant Mishra

Computer Science Department

University of Colorado at Boulder

Boulder, Colorado, USA

{jing,rhan,mishras}@cs.colorado.edu

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Jing Deng Richard Han Shivakant Mishra
Computer Science Department
University of Colorado at Boulder
Boulder, Colorado, USA
{jing,rhan,mishras}@cs.colorado.edu

Abstract

Wireless sensor networks are often constructed as asymmetric networks comprised of a large number of small, resource-constrained sensor nodes and a small number of relatively powerful base stations. A base station is vulnerable as a central point of failure in such networks. Typical packet traffic in a sensor network reveals pronounced patterns that allow an adversary analyzing packet traffic to deduce the location of a base station, which can then be disabled or destroyed. This paper investigates multiple anti-traffic analysis techniques aimed at disguising the location of a base station. First, a degree of randomness is introduced in the multi-hop path a packet takes from a sensor node to a base station. Second, random fake paths are introduced to confuse an adversary from tracking a packet as it moves towards a base station. Finally, multiple, random areas of high communication activity are created to deceive an adversary as to the true location of the base station. The paper evaluates these techniques analytically and via simulation using three evaluation criteria: total entropy of the network, total energy consumed, and the ability to guard against heuristic-based techniques to locate a base station.

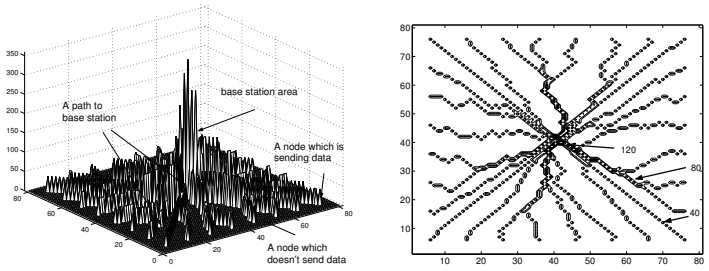
1 Introduction

A wireless sensor network (WSN) consists of a large number of small, resource-constrained sensor nodes, e.g. Berkeley MICA2 motes [11], and a small number of relatively powerful base stations, e.g. PC-caliber gateways. Each sensor node acts as an information source, sensing and collecting data samples from its environment. Each sensor node communicates this data to a base station via a multi-hop network in which each node performs routing functions.

Sensor data is typically routed along relatively fixed paths from sensor nodes towards the base station. This produces quite pronounced traffic patterns that reveal the direction towards and hence the location of the base station. Figure 1 illustrates the packet traffic volume forwarded by each node in the network with the shortest path routing scheme (we call it as SP scheme). The nodes nearer the base station clearly forward a significantly greater volume of packets than nodes further away from the base station, in the same manner that a river grows wider as it collects more water from its tributaries. Aggregator nodes that compress the data from multiple child nodes before forwarding upstream towards the base station can mitigate the pronounced increase in traffic volume towards the base station. However, the data traffic still accumulates towards the base station, if the aggregators send their data through multiple hops.

An adversary can analyze the traffic patterns revealed in Figure 1 to deduce the location of the base station within the WSN's topology. Since the base station is a central point of failure, once the location of the base station is discovered, an adversary can disable or destroy the base station, thereby rendering ineffective the data-gathering duties of the entire sensor network. Even if there are multiple base stations, an adversary can employ the same traffic analysis techniques to take out each base station one by one, until the entire network is disabled.

Even if the contents of data packets are encrypted, e.g. by pair-wise key schemes [8, 3, 7, 15, 25], an adversary can still deduce significant information by monitoring traffic volume and traffic path information in sensor network. Here, we identify two traffic analysis attacks in wireless sensor networks, *rate monitoring* attack and *time correlation* attack. In *rate monitoring* attack, an adversary can monitor the packet sending rate of nodes near the adversary, and always moves closer to the nodes that have a higher packet sending rate. In *time correlation* attack, an adversary observes the correlation in sending time between one node and a neighbor node that is assumed to be forwarding the same packet, and deduces the path by following the "sound" of each forwarding operation as the packet propagates towards the base station. Sensor nodes can defend this attack by buffering incoming packet for random period be-



(a) 3-D graph of data traffic. (b) Contour map of data traffic.

Figure 1. Pronounced data traffic patterns in a WSN reveal the location of the base station.

fore forwarding it. However, an adversary can pro-actively trigger the forwarding of packets by generating abnormal sensory events, e.g. abnormal temperature, that need to be forwarded as quickly as possible.

In this paper, we focus on developing countermeasures against traffic analysis attacks that seek to locate the base station, particularly the *rate monitoring* attack and *time correlation* attack. Without loss of generality, we consider sensor networks with a single base station. The anti-traffic analysis techniques proposed in this paper introduce randomized traffic volumes throughout the sensor network away from the base station, in order to deceive and misdirect an adversary so that the true path towards the base station cannot be easily found. Four anti-traffic analysis techniques are proposed to generate randomness. First, a multiple parent routing scheme is introduced that allows a sensor node to forward a packet to one of multiple parents. This makes the patterns less pronounced in terms of routing packets towards the base station. Second, a controlled random walk is introduced into the multi-hop path traversed by a packet through the WSN towards the base station. This distributes packet traffic, thereby rendering less effective rate monitoring attacks. Third, random fake paths are introduced to confuse an adversary from tracking a packet as it moves towards a base station. This mitigates the effectiveness of time correlation attacks. Finally, multiple, random areas of high communication activity are created to deceive an adversary as to the true location of the base station, which further increases the difficulty of rate monitoring attacks. We have analyzed our anti-traffic analysis techniques against rate monitoring and time correlation attacks. However, we believe that they can withstand other unforeseen traffic analysis attacks as well by virtues of providing increased randomness in communication patterns and increased deceptive mechanisms to confuse an adversary.

These anti-traffic analysis techniques are specially suited to the characteristics of wireless sensor networks, and exhibit several advantages. First, all four techniques are distributed in nature. There is no single initialization or coordination point involved to setup these mechanisms. Second, memory and computation requirements in each sensor node are relatively low, and can easily be met by modern sensors such as MICA2. Third, any compromise of one or a small number of sensor nodes by an adversary is easily tolerated. If an adversary compromises some nodes, the damage it can inflict upon the WSN is limited. Fourth, our techniques don't require a node to delay sending packets, as would be the case in standard de-correlation approaches. A node can send/forward its packet as soon as it is ready. This aids in reducing the time delay introduced by anti-traffic analysis techniques. Finally, the cost of these techniques is moderate and the techniques are applicable to large sensor networks. This is confirmed by the simulation results presented in the evaluation section.

Our techniques result in significantly delaying an adversary from finding a base station. This delay is useful in making WSNs more robust. For example, if an adversary has to spend T_a units of time to find one base station, an end user can continually use different base stations after every T_b time units, where $T_b < T_a$. In the absence of any anti-traffic analysis mechanisms, T_a is very small. As a result a user will have to change base stations very frequently. Since any change in base station consumes extra energy, e.g. to set up new routing paths, this will cost lots of energy. The most serious problem in our techniques is that they introduce extra messages in the network. Our experiments show that the number of messages increases by about 2 to 3 times, while the mechanisms delay the time of finding a base station by about 19 times. While energy is certainly critical in sensor networks, a tradeoff of significantly reducing the chances of a base station being located at the cost of reducing the battery lifetime by about half is quite reasonable for several applications, e.g. military applications.

The paper is organized as follows. In Section 2, the network model, threat model, and capabilities of sensor nodes are described. In Section 3, the probabilistic countermeasures embedded into routing algorithms are described, and

an analysis of their security under node-compromise is presented. In Section 4, algorithms are simulated and quantitatively measured in terms of their effectiveness and cost. Section 5 discusses related work, and finally, Section 6 concludes the paper.

2 Network Traffic and Threat Model

We assume the sensor network has a base station and a number of aggregator nodes. Each aggregator node processes data that it received from its group of local sensor nodes and sends that processed data to the base station through multiple hops.

For the capabilities of an adversary, we assume that an adversary can monitor network traffic, and launch a *rate monitoring attack* and a *time correlation attack*. An adversary can capture sensor nodes, compromise them and obtain all information, e.g. encryption keys, inside a node. Adversary can reprogram a node and convert it into a malicious node. However, we assume that adversary has to spend a certain amount of time to compromise a node, and so he can compromise only a small number of nodes in any reasonable period of time. Paricularly, the time that he can compromise all nodes along a path to base station is much longer than the the base station replacement time T_b. We also assume that an adversary can physically move from one location to another in the network. However, it doesn't have global information about the whole network, and cannot jam the entire network. Our scheme is useful for large sensor network, so if adversary just enters the network, he cannot see base station directly, although if he is close to base station, he can identify base station immediately. We call the area which adversary can immediately find base station as *base station area*.

We assume that sensor nodes use the key framework proposed in LEAP [25] to protect hop-by-hop communication. Nodes can set up pair-wise keys using existing protocols [8, 3, 7, 15, 25]. Every node can also set up a single cluster key [25] with all of its neighbor nodes. As described in [5], when a node sends a packet, it protects and encrypts the packet with its cluster key. An adversary cannot decrypt the contents of a packet. At the same time, other nodes in the cluster can easily understand the type of packet and process it accordingly.

In this paper, we focus on protecting the data traffic from aggregator nodes to base station through multiple hop routing. The local data traffic between sensor nodes and aggregator node can be protected by anti-traffic analysis schemes proposed in [5].

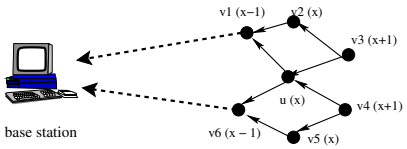


Figure 2. Neighbors and parents of node u. Figure shows node ID and its $level$ value. In SP, node u has one parent node v_1. In MPR, node u has two parent nodes, v_1 and v_6. In RW routing, u will forward packet to v_1 or v_6 with probability P_r, and with probability $1 - P_r$, it will randomly forward the packet to any neighbor node v_1 to v_6.

3 Anti-traffic analysis strategies

3.1 Multi-parent routing scheme

To reduce the starkness of pronounced paths, we modify the shortest path (SP) routing scheme shown in Figure 1 by having each node select one of multiple parent nodes to route data to the base station. When a node needs to forward a packet, the node randomly selects one of its parent nodes to forward the packet. We call this scheme multi-parent routing (MPR). We propose two methods for setting up multiple parents for each node. In the first method (See Figure 2), the beacon message sent by the base station contains a *level* field. The base station sets the value of *level* to 0. When a node forwards a beacon message, it increments it by 1. So the value of *level* represents the number of hops that a node is from the base station along a particular path. A sensor node s selects all neighbor nodes whose *level* value is less than s's *level* value as its parent nodes. In the second method, a node monitors all beacon messages it receives before forwarding the first beacon message. Since a node s has to wait for some amount of time before forwarding a beacon message (waiting time in MAC layer), it selects all nodes from whom it receives a beacon message while waiting to forward the first received beacon message as its parent nodes.

An adversary has several ways to attack these multi-parent routing setup schemes. A malicious node can claim a low *level* value to attract other nodes, and can use unfair media access control mechanisms to occupy the wireless channel. However, protecting routing schemes is beyond the scope of this paper. Here we assume that the routing set up scheme is relatively fast, so an adversary doesn't have enough time to attack routing set up process. Several mechanisms [14, 5] have already been proposed to protect against attacks to routng set up.

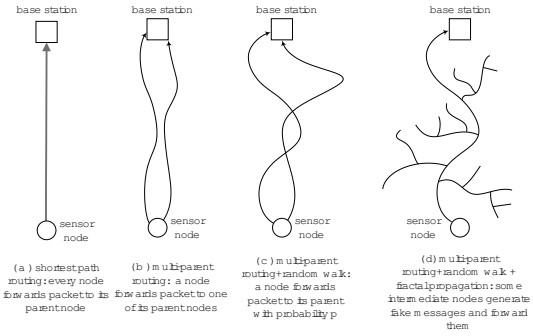


Figure 3. Techniques to counter anti-traffic analysis.

3.2 Random Walk

To further diversify routing paths and mitigate rate monitoring attacks, we propose a random walk (RW) routing scheme. In RW, when a node receives a packet, it forwards the packet to one of its parent nodes with probability p_r. However, it uses a random forwarding algorithm with probability $1-p_r$. In the random forwarding algorithm, the node forwards the packet to one of its neighbor nodes with equal probability. Like [13] and [23], MPR and RW use probabilistic routing. However, [13] and [23] use probabilistic routing for reliable data transmission in sensor networks, while we use probabilistic routing to defend against *rate monitoring attack*.

The RW technique results in some packets traversing a longer path to reach the base station than the shortest available path, as shown in Figure 3(c). This implies that RW will consume more energy per node on an average. To estimate how much extra energy is consumed by RW, we calculate the cost C of RW, where cost is defined as [5]: $C = \frac{M'}{M}$. Here, M' is the average number of hops a packet takes to reach the base station from an aggregator node in RW, and M is the number of hops a packet takes to reach the base station from the same aggregator node in SP. Clearly, M' depends on the several factors related to network topology, e.g. how many neighbors a sensor node has, how far the base station is from a sensor node or from one of its neighbor nodes, and so on. We calculate the value of C by making the following simplifying assumption. Suppose a node u randomly selects a neighbor node v to forward a packet. Assume that the distance (number of hops along the shortest path) between v and the base station is d, while the distance between u and base station is d'. We assume that the probability that $d > d'$ is same as the probability that $d < d'$. So on an average, when u forwards a packet to v, the distance from the base station doesn't change. Only when u forwards the packet to its parent node, the distance is reduced by 1. We denote n as the number of hops from the aggregator to the base station in SP, and n' as the number of average hops in RW. We have $n' \times p_r = n$. This implies $C = \frac{M'}{M} = \frac{1}{p_r}$.

In addition, a packet will take a longer time to reach the base station in RW. In fact, the extra time delay is directly related (linear) to the extra hops used for forwarding the packet. So, the time cost for each packet to reach the base station is roughly $\frac{1}{p_r}$ in RW.

3.3 Fractal Propagation

MPR and RW spread out data traffic and make it difficult to use a rate monitoring attack. However, RW is still vulnerable to *time correlation* attack. Usually, for a node s, the number of parent nodes is less than half of s's neighbor nodes, and for energy and efficiency considerations, typically $P_r > 0.5$. As a result, the possibility that a node forwards a packet to its parent node is higher than the possibility it forwards the packet to any one of its other neighbors. An adversary can exploit this to launch a time correlation attack, either by injecting abnormal report data or monitoring over a long period of time.

To address the shortcomings of MPR and RW, we propose a new technique called *fractal propagation*. In this technique, several *fake* packets are created and propagated in the network to introduce more randomness in the communication pattern. When a node hears that its neighbor node is forwarding a packet to the base station, the node generates a fake packet with probability p_c, and forwards it to one of its neighbor nodes. To control the propagation range of the fake packet, each newly generated fake packet contains a *length* parameter with value K. K is a constant that is known to all nodes, so an adversary cannot flood the whole network by sending fake packets with *length* parameter higher than K. When a node receives a fake packet, it decrements *length* by 1. If the value of *length* is greater than zero, the node forwards the fake packet to one of its neighbor nodes (not necessarily in the direction of the base station). If the value of *length* is zero, a node stops forwarding the fake packet. In addition, when a node hears that its neighbor node is forwarding a fake packet to someone else with *length* value k ($k < K$), it generates and forwards another fake packet with probability p_c and *length* value $k-1$.

These fake packets spread out in the network and their transmission paths form a tree (see Figure 3(d)). In particular, the communication traffic is much more spread out than RW. So even if an adversary can track a packet using time-correlation, she cannot track where the real (as opposed to fake) packet is going. This is because she cannot differentiate between a real and a fake packet without knowing the encryption key.

Suppose a node has x neighbor nodes on average. Let

$p_f = p_c \times x$ and $f(K)$ represents the total length of a fake tree that originated with *length* value K. We have

$$f(K) = p_f \times f(K-1) + f(K-1) + 1$$

Solving this recursive equation, we get

$$f(K) = \sum_{i=0}^{K-1} (p_f + 1)^i = \begin{cases} \frac{(p_f+1)^K - 1}{p_f} & \text{if } p_f > 0 \\ K & \text{otherwise} \end{cases}$$

Suppose the length of real path from the aggregator node to the base station is n. The cost is

$$C = \frac{n + n \times p_f \times \frac{(p_f+1)^K - 1}{p_f}}{n} = (p_f + 1)^K$$

If we combine RW and the fractal idea, the total cost is

$$C = \frac{(p_f + 1)^K}{p_r}$$

If we use fixed values of p_r, p_f and K, the average cost is a fixed value that is independent of the size of the network.

3.3.1 Fractal propagation with different forking probabilities

One problem with simple fractal propagation is that it generates a large amount of traffic near the base station. This potentially increases the packet collision rate and packet loss rate.

To address this problem, nodes can use different probabilities to generate fake packets. When a node forwards packets more frequently, it sets a lower probability for creating new fake packets. This technique is called Differential Fractal Propagation (DFP). The algorithm for setting this probability is as follows. When the packet forwarding rate r at a node is lower than a threshold h, the node generates new fake packets with probability p. When the packet forwarding rate is higher than h, the node generates new fake packets with probability $p' = p \times (h/r)^2$; h can be chosen as the packet sending rate of the aggregator node.

3.3.2 Enforced fractal propagation

The idea of fractal propagation aids significantly in spreading out the communication traffic evenly over the network and obfuscating any paths to the base station. To make matters worse for an adversary, we generate local high data sending rate areas, called *hot spots*, in the network. An adversary may be trapped in those areas and not be able to determine the correct path to base station. This routing technique is called Differential Enforced Fractal Propagation (DEFP). The challenge here is how to create hot spots that are evenly spread out in the network, such that only a minimum (preferably zero) amount of extra communication/coordination among the sensor nodes is needed.

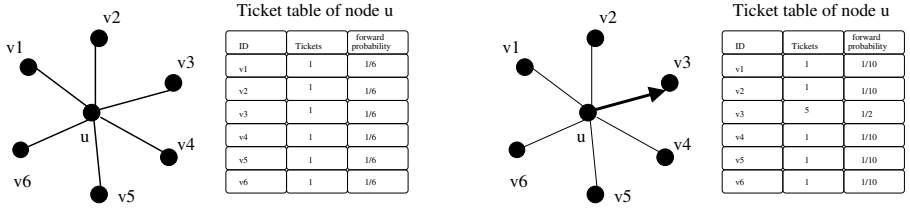
DEFP is a simple distributed algorithm based on DFP. The key idea is to let the nodes that forwarded fake packets earlier have a higher chance to forward fake packets in the future. In particular, if a node u forwarded a fake packet to another node v in the past, then it forwards the next fake packet received to v with a higher probability. The node uses a *lottery scheduling* algorithm [22] to choose the next node to forward the fake packet to. In this algorithm (see Figure 4), a node assigns tickets to each of its neighbor nodes. It chooses the next node to forward a fake packet to based on the number of tickets assigned to the neighbor nodes. A neighbor node with more tickets assigned has the higher probability of being chosen. In the beginning, all neighbor nodes are assigned one ticket. When the node chooses a neighbor node as the next node for forwarding a fake packet, it increments that node's tickets by k. This way, after a node has forwarded a fake packet to one of its neighbor nodes, it will continue to forward other fake packets to the same neighbor node with higher and higher probability. If an area of nodes receive fake packets, they are more likely to process more and more fake packets in the future. This will turn that area into a hot spot. It is also very easy to destroy current hot spots and reconstruct new hot spots at different places. For example, sensor nodes just reset the value of tickets to 1 when they receive a broadcast message from base station, and then start to build hot spots from beginning. To find an area is a hot spot, adversary needs to observe traffic in that area for a long time, and that will delay her to find location of base station.

3.3.3 Simulation

We simulated our anti-traffic analysis techniques in our simulator, which is based on a standard discrete event generator. Simulation results show that RW creates a more diffuse routing pattern than SP, while both fractal propagation techniques DFP and DEFP considerably obfuscate the location of the base station. Figure 5 shows the cumulative routes taken by packets through a sensor network employing DEFP. The network configuration for these simulations is a grid network described in Section 4.

3.4 Node Compromises

If an adversary compromises a node, she can find out the identity of its parent nodes, and read the contents of all packets passed through this node. In addition, by monitoring the traffic for some sufficiently long period time, she can obtain distribution information of all the ancestor nodes within her activity range. However, with this knowledge. she cannot determine the location of the base station, and



(a) before node u forwards any fake packet (b) after u forwards a fake packet to node v_3

Figure 4. Ticket table of node u

cannot block communication between an aggregator node and the base station. To determine the location of the base station, the adversary will have to compromise a large number of nodes along the path to the base station.

One attack against our scheme is to find the geographic direction of the base station by compromising two nodes at different locations. If each node's parent node is in the direction towards the location of the base station, an adversary can intersect the two direction vectors to determine the approximate location of the base station. However, this attack requires that the direction of a parent node be precisely towards base station, which is quite unlikely in a randomly distributed sensor network. In addition, MPR increases the difficulty in determining the precise geographic direction towards the base station, forcing the adversary to compromise many more nodes.

In fractal propagation, if an adversary compromises a node, she can find out whether a packet is a fake packet or real. However, she cannot obtain any information other than the ones discussed above (in RW case). An adversary can attempt to launch a DoS attack by generating many fake packets and forwarding them to flood the network. However, the propagation area of a fake packet is limited by the value of the *length* parameter. A fake packet can propagate and generate new fake packets only within a small part of the network, so the damage due to such DoS attack is limited.

Finally, an adversary can also generate several forged data packets and forward them to the base station in an attempt to flood the base station. However, mechanisms exist currently that allow intermediate nodes to filter out forged aggregation data, e.g. see [24, 26]. In SEF [24], intermediate nodes use randomly pre-distributed pair-wise keys to verify the authenticity of the data sent by the aggregator node. Any forged packets are filtered out by each intermediate node with certain probability and don't propagate over a long path.

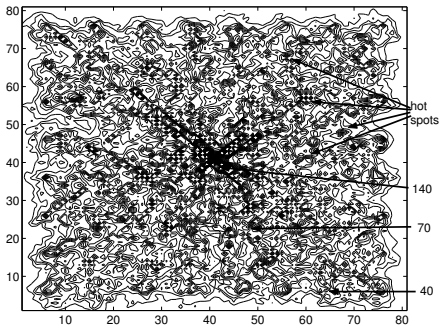


Figure 5. Number of packets sent/forwarded by each node in DEFP.

4 Evaluation

4.1 Evaluation Criteria

The main goal of anti-traffic analysis techniques is to prevent an adversary from tracking the location of a base station by analyzing communication patterns of a WSN over some reasonable period of time. Our goal is to make communication patterns as random as possible while minimizing costs, so that an adversary does not have sufficient information to deduce the location of the base station in a reasonable amount of time. Our evaluation focuses on how random the network traffic is, and the cost for our anti-traffic analysis schemes. We haven't simulated the effectiveness of defending against *time-correlation* attacks. A higher forking probability (P_f) and a longer $length$ of fake path will make it more difficult to launch a *time correlation* attack. Instead, we evaluate the the randomness of network traffic and effectiveness against *rate monitoring* attacks through two metrics —*entropy* of the network traffic and the *GSAT* test. To estimate the cost of our techniques, we count the number of messages exchanged in our techniques and compare them with the number of messages exchanged in SP. Since our techniques incur very little memory cost on each sensor node, e.g. keys and tickets of its neighbor nodes, we have not measured it in our simulation.

	Size	Average # Neighbors	Number of Aggregators	Sending Rate
Grid	81×81	8	28	4/minute
Random	4500	20	28	4/minute

Table 1. Network configuration Parameters

	Entropy		Traffic		Center Traffic	
	(SP)	(BR)	(SP)	(BR)	(SP)	(BR)
Grid	9.64	11.40	39000	7×10^6	10080	4×10^5
Random	8.20	12.08	21000	5×10^6	2792	1.8×10^5

Table 2. Entropy and Number of messages exchanged in SP and BR. (Traffic means the total messages exchanged in the network, and Center Traffic means the number of messages exchanged in the close vicinity of the base station.)

In addition to randomness, the exact values of entropy and the GSAT test depend on several other network characteristics, e.g. network structure, network size, number and location of aggregator nodes. To evaluate our techniques, we have focused on differences in entropy and GSAT test values measured under the cases when one of the proposed anti-traffic analysis techniques is used and the case when no anti-traffic analysis technique is used. We also experimented with different values of P_r in RW and P_f in DEFP, to understand the effects of these parameters. We simulated two network structures in our experiments: a grid topology and a random topology. Table 1 shows the parameters used in our simulation.

Entropy We use entropy to measure the randomness of network traffic. Entropy is a mathematical measure of information uncertainty, and it has been widely used as a metric to measure randomness in many applications, e.g. data communication, data compression, random number generators, and security of cryptographic algorithms. Entropy of a random variable X with a probability function $p(x)$ is defined as $H(X) = -\sum p(x)\log_2 p(x)$. Suppose that during a time period T, a sensor node a sent/forwarded p_a packets, and a total of M packets were sent/forwarded in the WSN N. We use the following formula to measure the entropy of N during the time period T: $H(N) = -\sum_{a\in N} \frac{p_a}{M}\log_2\frac{p_a}{M}$. In general, a higher value of $H(N)$ implies that the communication traffic pattern of N is more random.

GSAT Test The GSAT test is intended to measure the ability of a routing technique to guard against heuristic-based algorithms that an adversary may use to locate a base station. The GSAT algorithm [19] was proposed for solving NP-hard satisfiability problems, such as the 3SAT problem [4]. In contrast to the traditional deterministic solutions, GSAT is a probabilistic algorithm that combines a hill-climbing search algorithm with a random restart mechanism. GSAT can solve most of the large 3SAT instances in a short time.

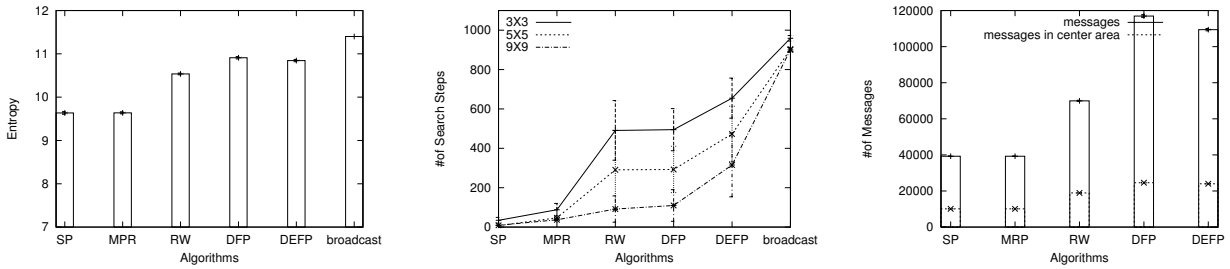
We use the idea of the GSAT algorithm to design a heuristic-based algorithm that an adversary uses to track the location of the base station. In this algorithm, an adversary starts at some location in the sensor network N. She monitors network traffic around her within her activity range. If she finds that a different node s within her activity range has the highest traffic, she moves to s, and continues to monitor traffic from s. Using this mechanism, she can move towards the locations that have higher and higher traffic volume. However, if she reaches a location that has the highest traffic with in the neighborhood (local maxima), she selects a direction at random, moves in that direction for some time, and then repeats the above algorithm. She continues to do this until she finds the base station.

The GSAT test measures the average number of hops an adversary takes to finally reach the base station using this heuristic algorithm. A large value of GSAT test implies that the routing technique has better potential to guard against heuristic-based algorithms that an adversary may use to locate a base station.

4.2 Effectiveness and Cost of Anti-Traffic Analysis Techniques

To evaluate the effectiveness of our anti-traffic analysis techniques, we simulated them over a grid network (see Table 1) and measured the values of entropy, GSAT test, and energy cost (number of messages exchanged). We simulated the following techniques: MPR, MPR+RW, MPR+RW+DFP, and MPR+RW+DEFP. For simplicity, we use MPR, RW, DFP, and DEFP respectively to refer to these techniques in the rest of the paper. In these simulations, we set P_r to 0.6, P_f to 0.2, and K to 6. To obtain an estimate of an upper bound of entropy and GSAT values, we simulated a routing mechanism in which every message sent by aggregator node is flooded to the entire network. We call this scheme a *broadcast*(BR) scheme. Since a broadcast scheme generates uniform network traffic, an adversary cannot obtain any clue about the location of base station. Table 2 shows the entropy values and number of messages exchanged in SP and broadcast schemes.

Figure 6 (a) shows the entropy measured for various routing techniques. All data reported here are an average over 20 runs. As expected, entropy is lowest for SP and highest for broadcast. Entropy for MPR and RW is higher than SP, but lower than DFP and DEFP. This shows that the idea of generating fake packets in a controlled manner



(a) entropy (b) GSAT test: number of search steps (c) message cost

Figure 6. Effectiveness and cost of anti-traffic analysis mechanisms.

does aid in making the network traffic pattern more random. This is in addition to the original goal of defending against time-correlation analysis.

To determine resiliency against a GSAT search, we simulated the data traffic and recorded the number of packets sent/forwarded by each node in a log file. We initialized a starting point for the adversary in the network and used the GSAT algorithm to discover the base station area. We recorded the number of steps the adversary takes to get into the base station area. For each log file, we set 81 different initial locations. For each initial location, we ran GSAT to search for the base station area for 100 times, and recorded the number of hops the adversary takes to get into the base station area. Finally, we computed the average number of hops the adversary takes to get into the base station area for each technique. In addition, we experimented with three different activity ranges of the adversary: adversary could monitor data traffic over 3×3, 5×5, and 9×9 areas around her respectively.

Figure 6 (b) shows the results of the GSAT test. First, we see that the GSAT values correlates with the entropy values shown in Figure 6 (a) (except DEFP). Higher entropy corresponds to a larger value of GSAT. This implies that both entropy and GSAT are useful metrics to measure the randomness in network traffic. The only exception is DEFP. Since DEFP converges some traffic together to form *hot spots*, it results in less entropy compared to DFP. However, those *hot spots* make it more difficult for an adversary to locate the base station using a GSAT search algorithm.

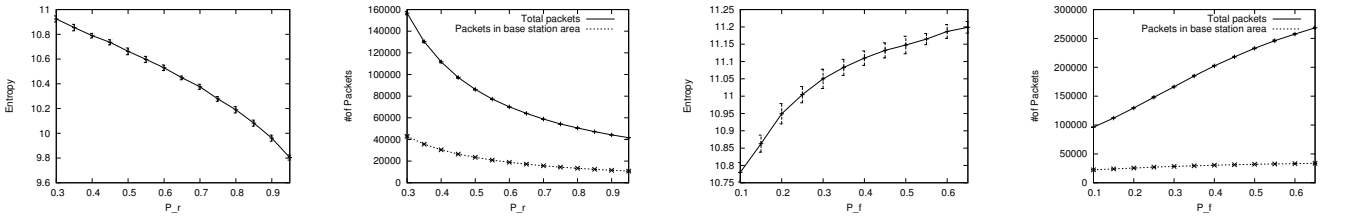
The activity range of an adversary also impacts the GSAT value. If the activity range is larger, the corresponding GSAT value is smaller. This implies that the adversary can find the base station in less number of hops. Also, we notice that anti-traffic analysis techniques significantly increase the number of steps an adversary has to take to locate the base station. For example, she can discover the base station area in 34 steps in SP (activity range 3×3), and 653 steps in DEFP, which is about 19 times more. Notice that the number of steps needed in *broadcast* method is only about 1.5 times the number of steps needed in DEFP approach. On the other hand, broadcast costs (number of messages) about 70 times more than DEFP. Even when the activity range of the adversary is large (9×9), our anti-traffic analysis techniques significantly increase the number of hops an adversary has to take to locate the base station area.

Figures 6 (c) shows the energy overhead of our techniques. We are interested in the overall energy overhead of the network, and also the energy overhead of nodes in the vicinity of the base station. The energy overhead is critical, because it affects the lifetime of a sensor node, as well as the packet loss rate caused by packet collisions. We are particularly interested in energy overhead in the nodes near the base station, because these nodes typically carry larger amounts of traffic, and any problem with these nodes may cause serious communication problems in the WSN.

Figure 6 (c) shows the total number of messages sent/forwarded by all nodes in the network, and the number of messages sent/forwarded by nodes near the base station (which is an area of 20×20 nodes with base station at center). The traffic in RW is about 1.8 times larger than the traffic in SP for the whole network and the area near the base station. The message cost of DFP and DEFP is about 2.8 times the message cost of SP in the whole network, and 2.4 times near the base station. In our simulation, when aggregators send four packets per minute, the nodes directly connected to the base station forward about 14 packets per minutes in SP, and about 34 packets per minute in DEFP. This is easily feasible in the current sensor network technology. Note that the message cost of these algorithms is constant, and doesn't increase with increase in network size.

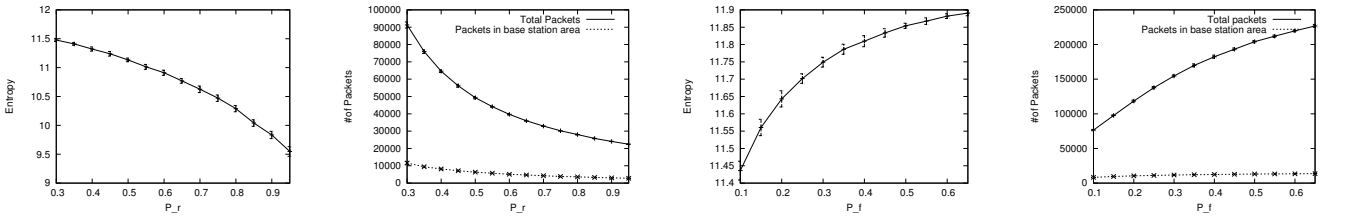
4.3 Effectiveness of P_r and P_f

To understand the effect of different values of P_r and P_f, we varied parameters for random walk RW and fractal propagation DEFP. We simulated them on both a grid network and a random network (Table 1). In RW, we varied P_r from 0.3 to 0.95. In DEFP, we fixed P_r at 0.6, and varied P_f from 0.1 to 0.65. The results are shown in Figures 7 and 8. From



(a) Entropy (RW) (b) Message overhead (RW) (c) Entropy (DEFP) (d) Message overhead (DEFP)

Figure 7. Effectiveness of P_r and P_f (Grid network).



(a) Entropy (RW) (b) Message overhead (RW) (c) Entropy (DEFP) (d) Message overhead (DEFP)

Figure 8. Effectiveness of P_r and P_f (Random network).

these figures, the variation in the values of entropy and message cost based on P_r and P_f is similar in both grid and random networks. In RW, the entropy sub-linearly decreases and the number of messages decreases with increasing P_r. In DEFP, entropy sub-linearly increases and the number of messages dramatically increases with increasing P_f.

These results imply that we should chose P_f as small as possible, as long as it satisfies our requirements. In Section 3, we analyzed the relation between message cost, and P_r and P_f. The results from these experiments imply that there is a relation between the entropy of network traffic, and P_r and P_f, which is independent of the size of the network. Another observation is that although the total number of messages exchanged is quite large for very large values of P_f, the number of messages exchanged near the base station doesn't change a lot. That shows the traffic control mechanism proposed in DFP (and used in DEFP) works quite well.

5 Related Work

Sensor network security has been a critical issue in sensor network research. e.g. secure data communcation [16], secure routing [14, 12, 5], and secure data aggregation [18], etc. In addition, much research has been performed in the area of setting up pairwise secret keys between different sensor nodes. Examples include [8, 3, 7, 15, 25].

In the area of privacy in E-commerce, many techniques have been developed to protect the anonymity of message senders and receivers. Our anti-traffic analysis techniques are similar to the methods used in traditional privacy and anonymity research, but we have 3 unique properties: First, we focus on hiding physical location of base station, instead of the identity of message sender or receiver. Second, the communication pattern in sensor network is highly asymmetric and converge on base station. That make it more difficult to protect base station against traffic analysis attack. Third, the communication and computing resources in traditional network are too expensive to current sensor network platform, so we cannot directly apply their mechanisms to sensor network.

In traditional privacy research, mist routing requires the pre-deployed, hierarchical and trusted routers [2]. [10] requires that every node can talk to every other node. The Onion routing protocol [9] disguises who talks to whom on the Internet by layered encryption and by forwarding received messages in a random order. In addition, a large number of messages are stored before forwarding them in a different order. A sensor node doesn't have enough memory to store many packets. The k-anonymous message transmission protocol proposed in [1] protects anonymity for both sender and receiver with low data transmission latency. Unfortunately, its high communication and computational requirements prevent it from being used in sensor networks. The techniques to disguise a receiver by routing each message to multiple receivers using a multicast mechanism are proposed in [17, 20]. Tor [6] is the second-generation onion router, which is a circuit-based low-latency anonymous communication service on the Internet. However, it needs to set up a large number of directory servers, which is difficult to envision in sensor networks.

Recently, A. Wadaa et. al proposed schemes to random-

ize communications during network setup phase, to protect anonymity of sensor network infrastructure [21]. In our work, we focus on defending against traffic analysis in data sending phase. In addition, we assume adversary can do some active attacks such as has inject traffic to the network, and compromising sensor nodes.

6 Conclusion

A base station controls the operation of a WSN, and naturally becomes a prime target of attack by adversaries. This paper addresses one aspect of protecting base stations by making it difficult for an adversary to locate a base station. The paper presents four anti-traffic analysis techniques, MPR, RW, DFP and DEFP that prevent the location of a base station from being easily discovered by an adversary. In MPR and RW, random walks and some amount of randomness are introduced in the multi-hop path a packet takes from a sensor node to a base station. In DFP, fractal propagation and random fake paths are introduced to confuse an adversary from tracking a packet as it moves towards a base station. Finally, in DEFP, multiple, random areas of high communication activity are created to confuse an adversary into searching in a wrong area. The paper evaluates these techniques analytically and via a simulation using three evaluation criteria: total entropy of the network, total energy consumed, and the ability to guard against heuristic-based techniques to locate a base station. The combination of random walks, fractal propagation, and hot spots are shown to increase the search effort required by an adversary to discover a base station.

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